# Littoral environmental reconnaissance using tactical imagery from unmanned aircraft systems

K. Todd Holland\*<sup>a</sup>, David M. Lalejini<sup>a</sup>, Steven D. Spansel<sup>a</sup>, Robert A. Holman<sup>a,b</sup>
<sup>a</sup>Naval Research Laboratory, Code 7430, Stennis Space Center, MS, USA 39529;
<sup>b</sup>College of Oceanic and Atmospheric Sciences, Oregon State University, Corvallis, OR USA 97331-5503

#### **ABSTRACT**

The dynamic nature of littoral regions requires a reconnaissance approach that can rapidly quantify environmental conditions. Inadequate estimation of these conditions can have substantial impacts on the performance of Naval systems. Given that expeditionary warfare operations can occur over timescales on the order of hours, exploitation of video imagery from tactical vehicles such as Unmanned Aircraft Systems (UAS) has proved to be a reliable and adaptive solution. Tactical littoral products that can be created by exploiting UAS imagery include estimates of surf conditions, dominant wave period, wave direction, nearshore currents, and bathymetry. These vehicles can fly for durations of 1-2 hours at altitudes of less than 1000 m (beneath typical cloud cover) to obtain imagery at pixel resolutions better than 1 m. The main advantage of using imaging sensors carried by these vehicles is that the data is available in the region of operational interest where other data collection approaches would be difficult or impossible to employ. The through-thesensor exploitation technique we have developed operates in two phases. The first step is to align individual image frames to a common reference and then georegister the alignment into a mapped image sequence. The second phase involves signal processing of pixel intensity time series (virtual sensors) to determine spatial relationships over time. Geophysical relationships, such as linear wave dispersion, can then be applied to these processed data to invert for environmental parameters such as bathymetry.

**Keywords:** littoral, remote sensing, bathymetry, unmanned vehicles

#### 1 INTRODUCTION

#### 1.1 Background

The remote determination of environmental parameters in the littoral zone has been an interest of both scientific and military communities for decades. A major factor in this determination is that the littoral environment is dynamic, having variability over many temporal and spatial scales, and it is dangerous in that in-situ sampling using instrumentation carries significant risk to the equipment and operational personnel responsible for deployment. Optical remote sensing provides a preferred solution to rapidly and accurately sample shallow water and surf zone conditions that have visible signatures. Figure 1, a video image of a littoral region, shows such signatures with identifiable parameters including wave propagation, surf, longshore currents, shoreline locations, and bathymetry. Aside from direct determination of conditions (littoral reconnaissance) to be used in mission planning, these same parameters can often serve as forcing or boundary conditions within numerical models to allow forecasting of additional environment parameters, possibly into the future as long as conditions are unchanged.

\*todd.holland@nrlssc.navy.mil; phone 1 228 688-5320;

Ocean Sensing and Monitoring II, edited by Weilin (Will) Hou, Robert A. Arnone, Proc. of SPIE Vol. 7678, 767806 · © 2010 SPIE CCC code: 0277-786X/10/\$18 · doi: 10.1117/12.852952

Proc. of SPIE Vol. 7678 767806-1

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1. REPORT DATE APR 2010		2. REPORT TYPE		3. DATES COVERED <b>00-00-2010 to 00-00-2010</b>			
4. TITLE AND SUBTITLE	5a. CONTRACT NUMBER						
Littoral environme	5b. GRANT NUMBER						
unmanned aircraft systems				5c. PROGRAM ELEMENT NUMBER			
6. AUTHOR(S)		5d. PROJECT NUMBER					
					5e. TASK NUMBER		
					5f. WORK UNIT NUMBER		
	ZATION NAME(S) AND AD ADDOCTOR	8. PERFORMING ORGANIZATION REPORT NUMBER					
9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)					10. SPONSOR/MONITOR'S ACRONYM(S)		
					11. SPONSOR/MONITOR'S REPORT NUMBER(S)		
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Form Approved OMB No. 0704-0188



Figure 1. Littoral snapshot image from Santa Rosa Island, FL obtained from an altitude of approximately 100 m above mean sea level. Intensity patterns associated with identifiable wave crests allow the determination of bathymetry, surf zone breaking patterns, and the shoreline.

Of particular interest is the exploitation of environmental sensing that can be easily configured for use with manned and unmanned airborne platforms. This concept extends back to operational requirements in World War II that lead to the development of algorithms to determine beach gradients from airborne photographs [1]. These algorithms were partitioned into two similar approaches. The first approach, known as the wave velocity method, utilizes photographs of wave patterns in combination with a geophysical relationship known as the linear dispersion relation to deduce water depths. This relation (in the absence of cross-shore directed mean currents) is commonly expressed in terms of wave celerity or phase speed c as:

$$c = \frac{\lambda}{T} = \sqrt{\frac{g\lambda}{2\pi} \tanh\left(\frac{2\pi h}{\lambda}\right)}$$
 (1)

where  $\lambda$  = wave length, T = wave period, and h = depth of water. Inversion of this equation yields depths in the direction of wave propagation for wave celerity values remotely sensed. In shallow water, where the depth is approximately less than 10% of the wave length, the inversion equation reduces to  $h = c^2/g$ . The wave velocity approach used two images collected over a known time interval to estimate the wave lengths and phase speeds used as inputs to equation (1). In the second approach, the wave period method, only a single image was required, where changes in measured wave lengths across the image were related to water depths under an assumption of narrow-banded swell wave propagation. The procedure was to measure wave lengths as far seaward as possible. These deep-water wave lengths were then used to determine T following the dispersion limit of  $\lambda = gT^2/2\pi$ . Knowing  $\lambda$  and T allowed solution for h in equation (1).

Both methods suffered from problems relating to wave crest determination, image scaling, timing inaccuracies and errors in geodetic mapping, which resulted in useful applications being limited to only a handful of occasions [1]. In fact in the same article (p. 91), Rear Admiral Wyatt, the Hydrographer to the Navy, is quoted as stating that "such a lot of flying has to be done to obtain photographs under just the right conditions that it would be a most expensive means of survey".

## 1.2 Recent Advances

Advances in littoral characterization using airborne remote sensing came with introduction of Fourier methods to estimate frequency and wave length from multiple image frames. This so called time series imagery (or more recently full motion video or "FMV") was a significant advantage over the WWII approaches in that the error associated with estimating shoaling wave frequency and wave length was greatly reduced. In addition, a more statistically robust

solution could be found by examining multiple wave periods as is common in a complex sea. Although the ability to estimate wave properties using this spectral approach was indicated as early as the 1960s (see [2]), extensive use of the dispersion method to estimate bathymetry from time series imagery did not occur until the late 1990s [3, 4] when imaging equipment and mapping procedures had improved. Although mostly limited to stationary platform such as towers, some littoral observations were obtained from manned aircraft [5, 6].

One important outcome of these methods relating to expected operational accuracy comes from the paper by [7] that used detailed pressure gauge observations to demonstrate, that outside of the surf zone, the linear dispersion relation is highly accurate, with average depth estimation errors on the order of 6% of the observed depth. Corroboration of these expectations using remotely sensed FMV data was provided by [8] where time series imagery from aircraft having a dwell of 2 minutes exhibited accuracies within approximately 95% of in situ truth. These similar findings indicate that Fourier methods of analyzing time series imagery are applicable for use in the bathymetry inversion problem. This approach (described next in section 2.1), serves as the basis for our littoral environmental reconnaissance products that can be derived from tactical imagery provided from unmanned aircraft systems.

#### 2 METHODS

#### 2.1 Spectral analysis of time series imagery

Although a number of approaches to analyzing littoral time series imagery have been proposed (see [9] for a summary), most follow a procedure that is generalized here. Given a time sequence of images, pixel intensities can be mapped to spatial dimensions I(x,y,t) using established photogrammetric transformations [10]. Typically the separation time between images is constant allowing straightforward application of spectral processing within the frequency domain, f. This is accomplished by computing a three-dimensional normalized Fourier Transform to allow the determination of cross-spectral coefficients  $C_{ij}$  over a number of pre-defined frequency bands and sensor positions (i,j). These coefficients effectively quantify the spatial phase relationships within the image in that intensity variations are assumed proportional to wave surface slopes, therefore tracking of coherent intensity variations is equivalent to imaging waves (height observations are not required to use the dispersion relation). A cross-spectral model of the wave field is then constructed as a spatially-temporally coherent superposition of traveling sinusoids as a function of wavenumber, k:

$$\hat{C}_{ij} = \exp\left(i\left(k_x \Delta x_{ij} + k_y \Delta y_{ij}\right)\right) \tag{2}$$

where  $k = 2\pi/\lambda$  and  $\Delta x$  and  $\Delta y$  are the separation distances between sensors. A weighted cost function can be established as  $w_{ij}|_{C_{ij}} - \hat{C}_{ij}|$  (with w, the spectral coherence) such that a nonlinear minimization can be applied to determine the best-fit k over multiple frequencies. These values are finally passed to the linear dispersion relation to estimate water depth, d, in which the inverted water depth best matches the propagation of all resolved gravity waves that follow the dispersion relationship. In our implementation, confidence intervals are also computed using the quality of the wavenumber minimization solution.

A number of pre-conditioning steps are typically performed on I(x,y,t) such as spatial trend normalization and temporal demeaning to minimize inter-frame gain fluctuations. An important constraint is the size of the analysis patch size used in the minimization as larger patches will lead to more robust estimates, however, since the bottom depth is typically regarded as constant within the analysis patch, fewer independent depth estimates. An initial guess of the deep-water wave direction relative to the Cartesian coordinate system is commonly provided and a frequency range of interest is selected to exclude temporal variability outside of what might include the dominant well peak. Typically wave lengths provided as seeds to the minimization algorithm are constrained within the algorithm to be within the deep water and shallow water (2-m) limits of the dispersion equation.

#### 2.2 Application to Unmanned Aircraft Systems

The Fourier analysis described above assumes that the imagery can be mapped accurately. For a stationary platform (such as a camera mounted on a tower) or for an aircraft with sophisticated positioning and inertial measurement hardware such as AROSS described by [11], this transformation can be accomplished effectively. Use of an Unmanned Aircraft System (UAS) for this purpose is an entirely different matter. Our goals were to work with UAS platforms commonly available operationally which includes the Tier I and Tier II classes of small, limited endurance UAS. With

wingspans of less than 3 m and total weights on the order of 5 kg (see Table 1), these SUAS systems were never designed to carry the advanced GPS or inertial measurement hardware used on manned aircraft that can often cost more than the aircraft system itself. While camera payload orientation and positional values are available in video-synchronized metadata streams, investigations have shown these data are insufficient to allow direct estimation of camera pointing angles for frame-by-frame georectification at required accuracies [12]. In practice, compass errors in azimuth of over 10 degrees are common and payload-to-payload variations are neglected through the use of a single set of calibration parameters.

Table 1. Small Unmanned Aircraft System (SUAS) Technical Specifications

Raven RQ11B SPECIFICATIONS*						
Physical dimensions:			Performance capabilities:			
Wingspan	1.4 m	(4.5 ft)	Range/Speed	10 km / 32–81 km/h		
Body length	0.9 m	(3 ft)	Endurance	60-110 min		
Weight	1.9 kg	(4.2 lbs)	Payload Fo	orward/side look EO/IR		
_	_		Maximum Altitu	ide 4267 m (14,000 ft)		
Deployment procedures:						
Hand launched; deep-stall landing.			*(from www.avinc.com)			

Because of these inaccuracies, we chose a somewhat dramatic deviation from traditional photogrammetric mapping procedures. Rather than mapping each individual frame to the ground plane using the supplied metadata (Figure 2, left), we implemented a frame alignment procedure that works with the video frames to provide relative matching transformations between any frame in the clip sequence and a user selected reference frame. The procedure uses the scale-invariant feature transform or SIFT algorithm suggested by [13] to provide the feature matching used in the alignment (Figure 2, right). The entire alignment is then mapped according to an optimized solution of the metadata associated with the matched features in the clip frames. This procedure, when applied to stable flight paths, provides a robust solution to the frame-to-frame inaccuracies.

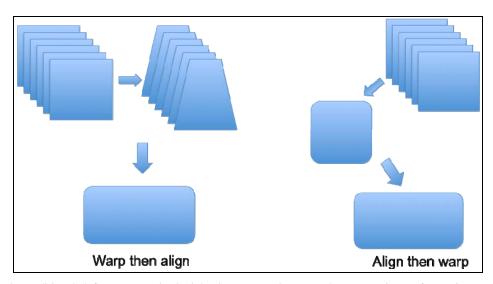


Figure 2. Traditional (left) versus revised (right) image mapping procedures. Raw image frame time series are designated as the stacks of squares. Given the inaccurate metadata associated with Small Unmanned Aircraft Systems, the revised procedure produced more robust image time series and image mosaics (rounded rectangles).

In addition to the modified mapping procedure, SUAS-based imagery collection presents additional challenges to littoral reconnaissance. For example, the large number of operational considerations relating to an unmanned aircraft flight in

terms of collection strategies and sensor performance is quite large. A simulation tool was developed to estimate the quality of bathymetric surfaces produced for a variety of remote sensing scenarios. This tool is based upon both theoretical and empirical relations [3, 7, 8] between wavenumber estimation accuracy and motion imagery collection parameter choices. The simulation variables involved include platform flight altitude, aircraft speed, grazing angle, lens horizontal field of view, number of horizontal and vertical pixels, number of desired bathymetry estimates, typical local water depth and typical local wavelength. An important use of these simulations, which corroborates previous findings, is that accuracy of the inversion method is largely dependent upon the image dwell and size of the spatial analysis region. An example is shown for a set of specific flight parameters in Figure 3. For this simulation, dwell over target is the critical parameter in that the estimated depth errors increase exponentially as the dwell decreases. We determined that the shortest useful dwell was on the order of 50 seconds to obtain depths with less than 20% error. Suitable spatial resolution and temporal sampling rates were more easily obtained using the SUAS hardware with pixel resolution and sample rate requirements being < 3 m and > 2 Hz respectively.

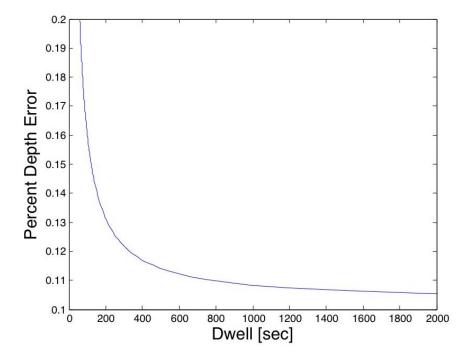


Figure 3. Optical Bathymetry Simulation for a SUAS flying at an altitude of 1500 m. Simulation shows bathymetric errors for wide field-of-view lens (20°) on gimbaled turret. Spatial coverage of imaged area is approximately 128 x 128 m. Larger field-of-view (or higher altitudes) will increase coverage, but eventually will decrease imaging resolution below what is required to observe wave crests.

# 3 RESULTS

# 3.1 Surrogate data results

Given the difficulty in obtaining flight permissions for unmanned aircraft operations in littoral regions, we leveraged existing video data of a littoral region obtained from a long-term camera deployment at Santa Rosa Island, FL. This station, part of the Argus network described by [14], provides high quality digital time series images that can be used to test the bathymetric inversion methods described in Section 2.1. In addition, high-resolution bathymetric surveys were completed on a quarterly basis using jetski-based equipment similar to that described by [15].

Approximately 250 video image sequences were selected for analysis under the criterion of having visible waves and being within +/- two weeks of a bathymetric survey. Each of these sequences, originally 10 minutes in duration, were

shortened to 50 seconds to be consistent with that expected for a SUAS flight data collection. Average computed wave directions were typically from 176 degrees relative to N, matching the onshore propagation direction perpendicular to the measured shoreline. Dominant wave periods ranged from 5.5 to 12.5 seconds and typical wave lengths at the offshore edge of the domain were on the order of 61 m. Depths in the imaged region varied between 2 and 12 m.

When compared to the surveyed bathymetry being used as ground truth, bathymetric errors were on the order of 13.5% of the measured depth. An example comparison is shown in Figure 4. While this estimate is slightly larger than the theoretical capability under optimal conditions (~6%), it is most likely representative of what can be obtained from full motion video provided by SUAS platforms being flown under operational scenarios. The average bias of these estimated surfaces from ground truth was 42 cm. In the calculation of these statistics, depths with estimated errors (based on the wavenumber minimization) were excluded.

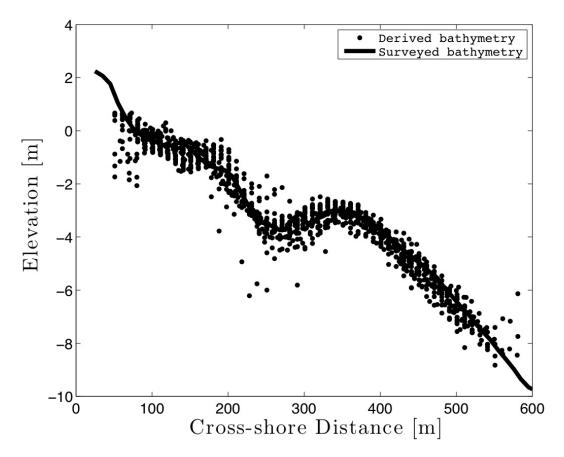


Figure 4. Simulated bathymetric inversion of UAS imagery provided by tower camera surrogate for validation of analytic approaches. Data from 29 January 2009, 1300 GMT.

#### 3.2 SUAS data results

An experiment was conducted 26-30 January 2009 at Santa Rosa Island, FL to test tactical environmental reconnaissance approaches, including remote bathymetry estimation using SUAS. The operational area extended approximately 4 km in the alongshore where bathymetric groundtruth was obtained using a variety of acoustic surveying methods. Actual data SUAS collection opportunities to validate the mapping and inversion approaches described above were limited to time periods where meteorological conditions were within flight thresholds (no rain, winds less than 20 knots, etc.) and oceanographic conditions showed visible wave signatures. Flight concepts of operations (or "conops") were developed to obtain imagery that could be used in a moasicing process to identify shorelines, sand bars and surf zones. An example

mosaic, created using the alignment process diagramed in Figure 2, is shown in Figure 5. From the figure, shoreline locations and even complex sand bar configurations can be determined visually. Algorithms have been developed to enable the automated extraction of these features by creating time-averaged and variance exposures where intensity changes such as between water and land are obvious.

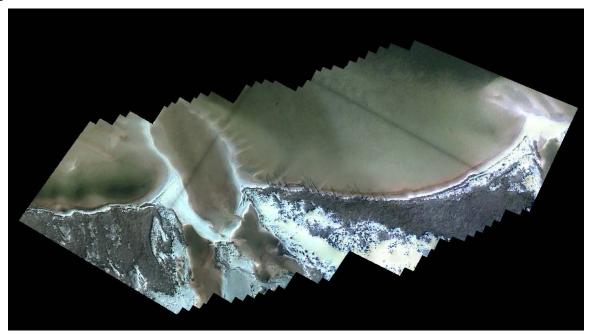


Figure 5. Geo-rectified mosaic from SUAS imagery obtained during overflight of Santa Rosa Island, FL on 27 January 2009.

The conops for the collection of similar image sequences to be analyzed for bathymetry were slightly different in that the flights were conducted starting over land centered on the shoreline to maximize look angle into the wave fronts and to maximize dwell. Unfortunately, out of the 10 sorties totaling approximately 8 hours flight time, visible wave patterns during this low energy period were insufficient to derive bathymetry. Maximum dwells over the surf zone were limited to less than 40 seconds. Follow-on exercises using alternate platforms are planned.

## 4 DISCUSSION

Over the past several years, there has been substantial research and development effort placed on the use of Unmanned Aircraft Systems to collect oceanographic information supporting littoral environmental reconnaissance. Significant progress has been made with respect to assessment of sensor quality and data analysis procedures. A robust procedure for creating mapped image sequences has been developed that uses image-to-image alignments prior to geo-rectification from optimized metadata. These procedures have allowed the rapid creation of impressive reconnaissance products such as mapped time-averaged mosaics. Shorelines, sand bars, and surf zones can be directly digitized from these type products. However, operational implementation of validated algorithms to derive wave angles, wave periods, wave lengths and bathymetry has been handicapped by platform instability that limits continuously dwell over a region to well less than what is required based on theoretical and empirical simulations. Based on the surrogate data analysis, our expectation is that a new class of airframe with a gimbaled camera will allow longer dwells of sufficient length to enable operational inversion of bathymetry using SUAS.

#### **ACKNOWLEDGEMENTS**

This work was supported by the Office of Naval Research through funding of the Naval Research Laboratory's project entitled "Estimation of Surf Zone Bathymetry using Small Unmanned Aircraft Systems", Program Element 0602435N. We are indebted to the civilian and military personnel who worked with us to conduct SUAS operations in some challenging environments.

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